# A family of rules for parameter choice in Tikhonov regularization of ill-posed problems with inexact noise level

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We consider linear ill-posed problems

$$Ax = y_*, \qquad y_* \in \mathcal{R}(A),$$

where  $A \colon X \to Y$  is a linear continuous operator between Hilbert spaces. The range  $\mathcal{R}(A)$  may be non-closed and the kernel  $\mathcal{N}(A)$  may be non-trivial.

- Assume that instead of exact data y\* only its approximation y is available.
- For approximation of the minimum norm solution  $x_*$  of the problem  $Ax = y_*$  we use the Tikhonov regularization method

$$x_{\alpha} = (\alpha I + A^*A)^{-1}A^*y.$$



#### Information about noise level

- In the following we consider three cases of knowledge about noise level for  $||y y_*||$ :
  - Case 1: exact noise level  $\delta$ :  $||y y_*|| \le \delta$ .
  - Case 2: no information about  $||y y_*||$ .
  - Case 3: approximate noise level: given is  $\delta$  but it is not known whether the inequality  $\|y-y_*\| \leq \delta$  holds or not. For example, it may be known that with high probability  $\delta/\|y-y_*\| \in [1/10,10]$ . This very useful information should be used for choice of  $\alpha = \alpha(\delta)$ .
- Choice of regularization parameter  $\alpha$ .
  - Rules for the Case 1 (discrepancy principle, etc.) need exact noise level: rules fail for very small underestimation of the noise level and give large error  $\|x_{\alpha} x_{*}\|$  already for 10% overestimation.
  - Rules for the Case 2 do not guarantee the convergence  $x_{\alpha} \to x_*$  for  $\|y y_*\| \to 0$ .
  - Our rules for the Case 3 guarantee  $x_{\alpha} \to x_*$  as  $\delta \to 0$ , if  $\lim_{\delta \to 0} \frac{\|y y_*\|}{\delta} \le \text{const.}$



#### Parameter choice rules for the case of exact noise level

- Discrepancy principle (D):  $\alpha_D$  is the solution of  $d_D(\alpha) := ||Ax_\alpha y|| = C\delta$ ,  $C \ge 1$ .
- Monotone error rule (ME):

$$d_{\mathsf{ME}}(\alpha) := \frac{\|B_{\alpha}(Ax_{\alpha} - y)\|^2}{\|B_{\alpha}^2(Ax_{\alpha} - y)\|} = \delta,$$

$$B_{\alpha} = \sqrt{\alpha}(\alpha I + AA^*)^{-1/2}.$$

#### Family of rules for parameter choice

Fix q, l, k such that  $3/2 \le q < \infty$ ,  $l \ge 0$ ,  $k \ge l/q$ ; 2q, 2k,  $2l \in \mathbb{N}$ . Choose  $\alpha = \alpha(\delta)$  as the largest solution of

$$d(\alpha \mid q, l, k) := \frac{\kappa(\alpha) \|D_{\alpha}^k B_{\alpha}(Ax_{\alpha} - y)\|^{q/(q-1)}}{\|D_{\alpha}^l B_{\alpha}^{2q-2}(Ax_{\alpha} - y)\|^{1/(q-1)}} = b\delta,$$

where  $B_{\alpha} = \sqrt{\alpha}(\alpha I + AA^*)^{-1/2}$ ,  $D_{\alpha} = \alpha^{-1}AA^*B_{\alpha}^2$ ,

$$\kappa(\alpha) = \begin{cases} 1, & \text{if } k = I/q, \\ (1 + \alpha ||A||^{-2})^{\frac{kq - I + q/2}{q - 1}}, & \text{if } k > I/q, \end{cases}$$
 (1)

$$\downarrow \alpha \to 0$$
1 (2)

$$b \approx \left(\frac{3}{2}\right)^{\frac{3}{2}} \frac{k^k}{(k+3/2)^{k+3/2}} \left(\frac{k^k (l+3/2)^{l+3/2}}{l^l (k+3/2)^{k+3/2}}\right)^{\frac{2}{q-1}}.$$
 (3)

Denote this rule by R(q, l, k).

#### Examples of this family of rules

- Modified discrepancy principle (Raus 1985, Gfrerer 1987): q = 3/2, l = k = 0
- Monotone error rule (Tautenhahn 1998): q = 2, l = k = 0
- Rule R1 (Raus 1992): q = 3/2, k = l > 0
- Balancing principle (Mathé, Pereverzev 2003) can be considered as an approximate variant of rule R1 with k=1/2.

#### Existence of solution for family of rules

- If k>l/q, then the equation  $d(\alpha\mid q,l,k)=b\delta$  has a solution for every  $b={\rm const}>0$ , because  $\lim_{\alpha\to\infty}d(\alpha\mid q,l,k)=\infty$  and  $\lim_{\alpha\to 0}d(\alpha\mid q,l,k)=0$ .
- ② If k = l/q, then the solution of the equation  $d(\alpha \mid q, l, k) = b\delta$  exists, if  $b \ge b_0(q, l, k)$  and  $||y y_*|| \le \delta$ .

#### Convergence and stability

- Convergence. Let  $k \ge l/q$ . Let the parameter  $\alpha = \alpha(\delta)$  be the solution of the equation  $d(\alpha \mid q, l, k) = b\delta$ ,  $b > b_0(q, l, k)$ . If  $||y y_*|| \le \delta$ , then  $||x_\alpha x_*|| \to 0$   $(\delta \to 0)$ .
- **Stability** (with respect to the inaccuracy of the noise level). Let k > l/q. Let the parameter  $\alpha(\delta)$  be the **largest** solution of the equation  $d(\alpha \mid q, l, k) = b\delta$ . If  $\frac{\|y y_*\|}{\delta} \le c = \text{const}$  in the process  $\delta \to 0$ , then  $\|x_\alpha x_*\| \to 0$  ( $\delta \to 0$ ).

#### Quasioptimality

Let  $l/q \le k \le l \le q/2$ . Let the parameter  $\alpha(\delta)$  be the **smallest** solution of the equation  $d(\alpha \mid q, l, k) = b\delta$ . Then the rule is **quasioptimal**:

$$\|x_{\alpha}-x_{*}\|\leq C(b)\inf_{\alpha\geq 0}\left\{\|x_{\alpha}^{+}-x_{*}\|+\frac{\delta}{2\sqrt{\alpha}}\right\},$$

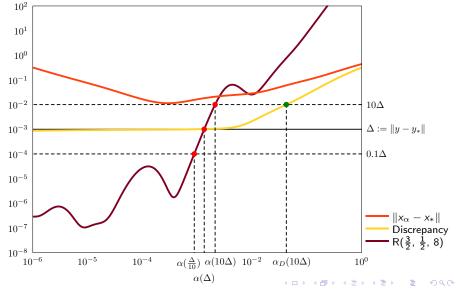
where  $x_{\alpha}^+$  is the approximate solution with exact right-hand side. It holds  $\sup_{\|y-y_*\|\leq \delta}\|x_{\alpha}-x_{\alpha}^+\|\leq \frac{\delta}{2\sqrt{\alpha}}$ 

- Largest solution ⇒ stability
- Smallest solution ⇒ quasi-optimality
- If the solution is unique, quasi-optimality also holds for the largest solution. In most of our numerical experiments the solution was unique.

In the following we choose the largest solution.



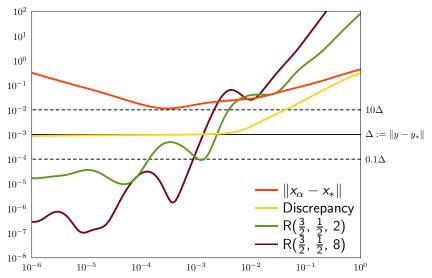
### Stability of choice $\alpha = \alpha(\delta)$ from rule $d(\alpha) = \delta$



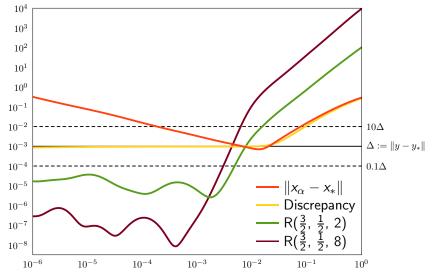
#### Stability of parameter choice

- Compare rules for choice of the regularization parameter  $\alpha = \alpha(\delta)$  as the solution of the equation  $d(\alpha) = b\delta$ .
- The stability of parameter choice rule with respect to the inaccuracy of noise level information increases for increasing  $d'(\alpha)$  in the neighbourhood of  $\alpha(\|y-y_*\|)$ .
- In many rules from the family  $d'(\alpha)$  is much larger than in the discrepancy principle, thus these rules are more stable with respect to inaccuracies of noise level  $\delta \approx \|y-y_*\|$ .
- The previous slide and the following 3 slides show the behaviour of functions  $d(\alpha)$  in the problem 'phillips' from Hansen's Regularization Tools.

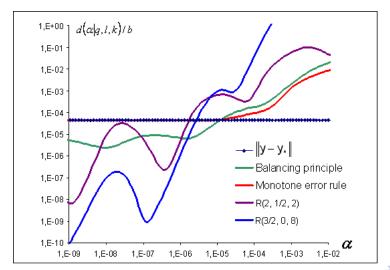
#### Behavior of functions $d(\alpha)$ in rules $d(\alpha) = \delta$ , p = 0



### Behavior of functions $d(\alpha)$ in rules $d(\alpha) = \delta$ , p = 2



# Behaviour of function $d(\alpha)$ in the neighbourhood $\alpha(||y-y_*||)$ , p=0





#### Hansen's test problems used in numerical tests.

Set I of test problems, P. C. Hansen's Regularization Tools.

Nr	Problem	cond <sub>100</sub>	selfadj	Description
1	baart	5e+17	no	(Artificial) Fredholm integral equation
				of the first kind
2	deriv2	1e+4	yes	Computation of the second derivative
3	foxgood	1e + 19	yes	A problem that does not satisfy the disc-
				rete Picard condition
4	gravity	3e + 19	yes	A gravity surveying problem
5	heat	2e + 38	no	Inverse heat equation
6	ilaplace	9e+32	no	Inverse Laplace transform
7	phillips	2e+6	yes	An example problem by Phillips
8	shaw	5e + 18	yes	An image reconstruction problem
9	spikes	3e + 19	no	Test problem whose solution is a pulse
				train of spikes
10	wing	1e + 20	no	Fredholm integral equation with discon-
				tinuous solution

#### Brezinski-Rodriguez-Seatzu problems

Set II of test problems, Numerical Algorithms 2008, 49, 1-4, pp 85-104.

Nr	Problem	cond <sub>100</sub>	selfadj	Description
11	gauss	6e+18	yes	Test problem with Gauss matrix $a_{ij} =$
				$\sqrt{rac{\pi}{2\sigma}}e^{-rac{\sigma}{2(i-j)^2}}$ , kus $\sigma=0.01$
12	hilbert	4e + 19	yes	Test problem with Hilbert matrix $a_{ij} =$
				$\frac{1}{i+j-1}$
13	lotkin	2e+21	no	Test problem with Lotkin matrix (same
				as Hilbert matrix, except $a_{1j}=1)$
14	moler	2e+4	yes	Test problem with Moler matrix $A =$
				$B^TB$ , where $b_{ii}=1$ , $b_{i,i+1}=1$ , and
				$b_{ij}=0$ otherwise
15	pascal	1e + 60	yes	Test problem with Pascal matrix $a_{ij} =$
				$\binom{i+j-2}{i-1}$
16	prolate	1e + 17	yes	Test problem with a symmetric, ill-
				conditioned Toeplitz matrix

### Solution vectors for BRS-problems

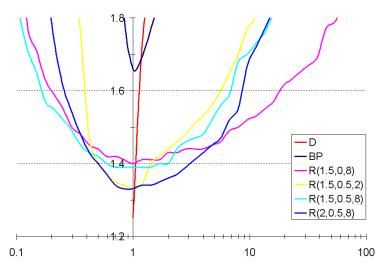
Description	$\overline{X}_i$
constant	1
linear	$\frac{i}{N}$
quadratic	$\left(\frac{i-\left\lfloor\frac{N}{2}\right\rfloor}{\left\lceil\frac{N}{2}\right\rceil}\right)^2$
sinusoidal	$\sin \frac{2\pi(i-1)}{N}$
linear+sinusoidal	$\frac{i}{N} + \frac{1}{4}\sin\frac{2\pi(i-1)}{N}$
step function	$\begin{cases} 0, & \text{if } i \leq \left\lfloor \frac{N}{2} \right\rfloor \\ 1, & \text{if } i > \left\lfloor \frac{N}{2} \right\rfloor \end{cases}$

#### Perturbed data and presentation of results

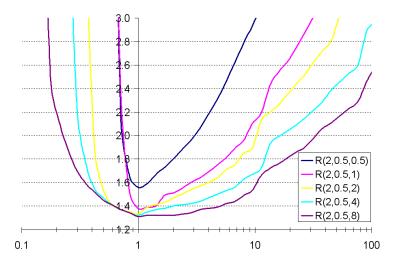
- Besides solution  $x_*$  also smoother solution  $x_{*,p} = (A^*A)^{p/2}x_*$  with  $y_* = Ax_{*,p}$ , p = 2 was used.
- The problems were normalized, so that Euclidean norms of the operator and the right hand side were 1.
- For perturbed data we took  $y=y_*+\Delta$ ,  $\|\Delta\|=0.3,\,10^{-1},\,\ldots,\,10^{-6}$  with 10 different normally distributed perturbations  $\Delta$  generated by computer.
- Problems were solved by Tikhonov method, assuming that the noise level is  $\delta = \varrho \|y y_*\|$ . Thus  $\varrho > 1$  corresponds to overestimation of the true error,  $\varrho < 1$  to underestimation.
- To compare the rules, we present averages (over problems, perturbations  $\Delta$  and runs) of error ratios  $\|x_{\alpha} x_{*}\|/e_{\text{opt}}$ , where  $e_{\text{opt}}$  is minimal error in Tikhonov method.



# Stability of the rules with respect to $\varrho = \frac{\delta}{\|y-y_*\|}$

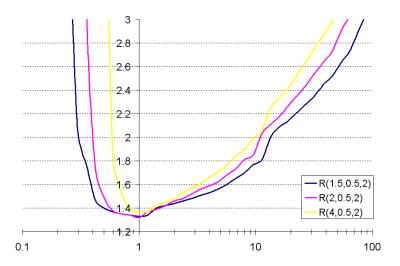


## Stability of rule R(q, l, k) increases if k increases

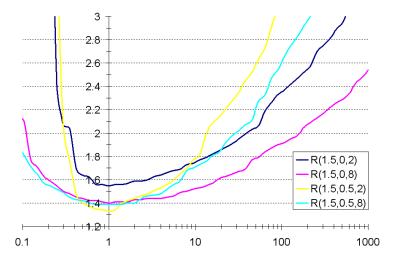




## Stability of rule R(q, l, k) increases if q decreases



### I=0.5 is recommended (I=0 is good if $\delta\gg \|y-y_*\|$ )



# Post-estimation of regularization parameter in case

$$||y - y_*|| \le \delta$$

- $\alpha_{\mathsf{ME}} \geq \alpha_{\mathsf{opt}} := \mathrm{argmin}\{\|x_{\alpha} x_*\|, \ \alpha \geq 0\}$ , computations suggest  $\alpha_{\mathsf{MEe}} = 0.4\alpha_{\mathsf{ME}}$ , if  $\|y y_*\| = \delta$ .
- More stable with respect to overestimation of noise level is the choice  $\alpha_{\text{Me}} = \min(\alpha_{\text{MEe}}, 1.4\alpha_{\text{R}(\frac{3}{2}, \frac{1}{2}, 2)}), \ b = 0.023.$

### Heuristic rules (not using $\delta$ ) in Tikhonov method

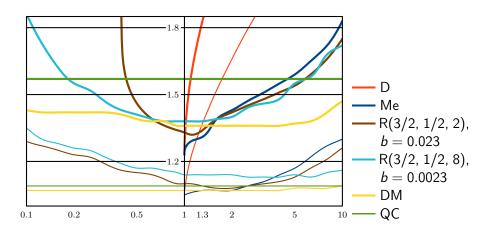
- Quasioptimality criterion Q: take  $\alpha$  as the global minimizer of the function  $\psi(\alpha) = \|x_{\alpha} x_{2,\alpha}\|$ , where  $x_{2,\alpha}$  is 2-iterated Tikhonov approximation  $x_{2,\alpha} = (\alpha I + A^*A)^{-1}(\alpha x_{\alpha} + A^*y)$ . Sometimes this gives too small  $\alpha$ , therefore we try to find a lower bound of minimization interval, determined during computations.
- Rule QC. Make computations on the sequence of parameters  $\alpha_i=q^{i-1},\ i=1,\ 2,\ \ldots;\ q<1,$  for example, q=0.9. Take  $\alpha_i$  as the minimizer of the function  $\psi(\alpha_i)=\|x_{\alpha_i}-x_{2,\alpha_i}\|$  in the interval  $[\underline{\alpha},1],$  where  $\underline{\alpha}$  is the largest  $\alpha_i$ , for which the value of  $\psi(\alpha_i)$  is C=5 times larger than its value at its current minimum.
- L-curve rule, GCV-rule, Hanke-Raus rule and Brezinski-Rodriguez-Seatzu rule gave in our numerical experiments not so good results as rules Q and QC.

#### Rule DM for approximate noise level in Tikhonov method

#### Rule DM for Tikhonov method

- 1) Make computations on the sequence of parameters  $\alpha_i = q^{i-1}$ ,  $i = 1, 2, \ldots$ ; q < 1, for example, q = 0.9; find  $\underline{\alpha}$  as the first  $\alpha_i$  for which  $\sqrt{\alpha_i} \|x_{\alpha_i} x_{2,\alpha_i}\| \le c_1 \delta$ ,  $c_1 = \text{const}$ ;
- 2) find  $\alpha_i = \operatorname{argmin} \frac{(1+\alpha\|A\|^{-2})\|D_{\alpha}^{1/2}B_{\alpha}(Ax_{\alpha}-y)\|^2}{\alpha^{\epsilon 2}\|D_{\alpha}^{1/2}B_{\alpha}^2(Ax_{\alpha}-y)\|}$  in  $[\underline{\alpha},1]$ ,  $c_2 = \operatorname{const.}$
- If  $\varrho := \delta/\|y y_*\| \in (0.1, 10)$ , then we recommend  $c_1 = 0.005$ ,  $c_2 = 0.05$ ; if less information is known,  $\varrho \in (0.01, 100)$ , then we recommend  $c_1 = 0.001$ ,  $c_2 = 0.47$ .
- Convergence  $x_{\alpha} \to x_*$ , as  $\delta \to 0$ , provided that  $\lim \|y y_*\|/\delta \le C$ , is guaranteed. If  $x_* \in \mathcal{R}((A^*A)^{p/2})$ , then for rule DM with  $c_1 \ge 0.24$  the error estimate  $\|x_{\alpha} x_*\| \le \text{const } \delta^{p/(p+1)}$  holds for all  $p \le 2$ .

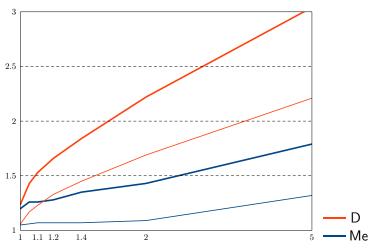
Averages (thick lines) and medians (thin lines) of error ratios in various rules in dependence of  $\varrho = \delta/\|y - y_*\|$ 



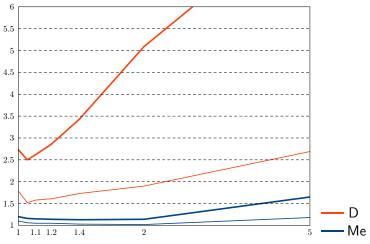
# Preferences of rules in dependence of the accuracy of noise level information $\varrho = \delta/\|y - y_*\|$

- If we are sure that  $\varrho \in [1, 1.5]$ , then we recommend the rule Me.
- In case  $\varrho \in [0.6, 1.5]$  we recommend the rule R(3/2, 1/2, 2), b = 0.023.
- If less information about the noise level is known, for example,  $\varrho \in [1/20, 20]$ , then we recommend the rule DM.
- For even less information about the noise level, we recommend the rule QC. If  $\|Ax_{\alpha_{\rm QC}}-y\|$  is evidently less than  $\|y-y_*\|$ , then we recommend to decrease the constant C, for example, using (C+1)/2 instead of C.

Averages (thick lines) and medians (thin lines) of error ratios in rules D and Me in dependence of  $\varrho = \delta/\|y - y_*\|$ , p = 0



Averages (thick lines) and medians (thin lines) of error ratios in rules D and Me in dependence of  $\varrho = \delta/\|y - y_*\|$ , p = 2



#### Conclusions

- We propose a family of rules R(q, l, k) for approximate noise level, where  $3/2 \le q < \infty$ ,  $l \ge 0$ ,  $k \ge l/q$ , 2q, 2k,  $2l \in \mathbb{N}$ .
- If k > l/q and  $\frac{\|y-y_*\|}{\delta} \le C = \text{const as } \delta \to 0$ , then we have  $\|x_{\alpha} x_*\| \to 0 \ (\delta \to 0)$ .
- Certain rules from the family gave in numerical experiments good results in case of several times over- or underestimated noise level.

#### Bibliography

- U. Hämarik, R. Palm, and T. Raus. On minimization strategies for choice of the regularization parameter in ill-posed problems. *Numerical Functional Analysis and Optimization*, 30(9&10):924–950, 2009.
- U. Hämarik and T. Raus. About the balancing principle for choice of the regularization parameter. *Numerical Functional Analysis and Optimization*, 30(9&10):951–970, 2009.
- 3 T. Raus and U. Hämarik. New rule for choice of the regularization parameter in (iterated) Tikhonov method. *Mathematical Modelling and Analysis*, 14(2):187–198, 2009.
- R. Palm. Numerical comparison of regularization algorithms for solving ill-posed problems. PhD thesis, University of Tartu, 2010. http://hdl.handle.net/10062/14623.
- U. Hämarik, R. Palm, and T. Raus. Comparison of parameter choices in regularization algorithms in case of different information about noise level. *Calcolo*, 48(1):47–59, 2011.
- U. Hämarik, R. Palm, T. Raus. A family of rules for parameter choice in Tikhonov regularization of ill-posed problems with inexact noise level. *Journal of Computational and Applied Mathematics*, 2011. Accepted. doi:10.1016/j.cam.2011.09.037